Compound Noun Decomposition Using a Markov Model

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Abstract
A statistical method for compound noun decomposition is presented. Previous studies on this problem showed some statistical information are helpful. But applying statistical information was not so systemic that performance depends heavily on the algorithm and some algorithms usually have many separated steps. In our work statistical information is collected from manually decomposed compound noun corpus to build a Markov model for composition. Two Markov chains representing statistical information are assumed independent: one for the sequence of participants’ lengths and another for the sequence of participants’ features. Besides Markov assumptions, least participants preference assumption also is used. These two assumptions enable the decomposition algorithm to be a kind of conditional dynamic programming so that efficient and systemic computation can be performed. When applied to test data of size 5027, we obtained a precision of 98.4%.

1 Introduction
Generally, compound noun takes the form of successive appearance of elementary nouns. Decomposition of compound nouns is an important problem in natural language processing (NLP), especially in oriental languages such as Korean, Chinese, Japanese in that there can be no intervening blank between participant nouns. It is more complicated in Korean case, since most Korean words are represented by phonetic alphabets. To analyze the meaning of a Korean compound noun, its decomposition is necessary. Only with dictionary lookup, several compositions of a compound noun are possible. Finding all possible candidate compositions [3] is of high cost since the number of compositions increases exponentially in proportion to the length of the compound noun. Although the length of many compound noun is usually manageable, some heuristic search is required in order to avoid full search, for search involves dictionary lookup. Even after all the candidates possible are found, semantically correct one must be selected by some semantic resolver. If heuristics are adopted, selection choices can be made before complete participants of a candidate are searched.

Some heuristics on this problem have been studied before. One of the simplest heuristics is longest match first heuristics. With this method, decomposition points are searched from left to right and the next decomposition point is the end point of longest elementary noun starting at the previous decomposition point. On the other hand, there is a different method in which the most probable decomposition point is found in the whole string, and then this decomposition is performed on the substrings recursively [2]. If algorithms like these did not have a backtracking mechanism they would frequently fall in local maxima, resulting in low accuracy. Some flexible heuristics that reduces the number of search paths and partially allows backtracking are studied [5, 2, 9]. But in these approaches models can not completely specify the decomposition process and performance depends heavily on the algorithm implemented and usually have exception handlers or multiple steps.

Many useful statistical information for selection among candidates or the next composition position were proposed as well. These information include mutual information between syllables [2], syllable pattern of com-
compound nouns [9], similarity/disimilarity between term distribution [6], word collocation and mutual information [4], lexical frequencies [3]. Mutual information between syllables is closely related to the syllable composition statistics in a lexicon but rarely represents the semantic relationship among elementary nouns in compound noun. Syllable pattern of compound nouns need some exception handler owing to the variety in the number of participants. Lexical frequencies are not specific to compound nouns. So it may not represent the statistical information of compound nouns. Except when selections among completely decomposed candidates are performed, the statistical information itself works as heuristics for reducing search space, too. All the methods mentioned above require large corpus for collection statistical information. But the sizes of corpus have wide ranges due to which statistical information should be used. In this paper we propose two Markov chains assumed independent and least participants preference assumption both as a heuristics and a selection measure. Each Markov chain represents the sequence tendency in the sense of participant's semantic feature and participant's length respectively. Fundamentally while full search is performed, if assumptions we proposed are satisfied, the premature determination is made so that the whole process takes the form of conditional dynamic programming scheme. The basic idea behind this approach is that the participants of compound noun would have some relationship with each other and when given these statistical information, the chances of other factors such as the algorithm could be excluded.

2 Compound Nouns

In our framework, compound nouns may comprise somewhat involved patterns. It is a string which has no blank character in it. Its components are to be nouns, prefixes, suffixes which can be found in dictionary, and recursively compound nouns. Furthermore, in our definition, compound nouns can be followed by a postposition, which cases show up frequently and are hard to be distinguished from the other cases. Representing formally in syntactic form, compound noun can be of the following form.

\[
\text{elementary } C \text{noun} := (\text{prefix})^* (\text{noun})^* (\text{suffix})^* \\
C \text{noun} := (\text{elementary } C \text{noun})^* (\text{postposition})^*
\]

where every element of the sets prefix, noun, suffix, postposition is in dictionary and \((L)^+\) denotes "zero or more concatenations of" \(L\) and \((L)^*\) denotes "one or more concatenations of" \(L\). The problem of compound noun decomposition is to select a syntactically and semantically correct sequence of elements in \(\text{prefix} \cup \text{suffix} \cup \text{noun} \cup \text{postposition}\) given a string \(C \text{noun}\) defined above. We will refer the components of a compound noun to its participants in the rest of this paper.

For example, if we’re given a C noun string “중국의 전통 문화” then after decomposition, “중국(official)” + “의(usage)” + “문화(bill)” sequence should be found and selected even though “중국(official)” + “의(usage)” + “문화(inside)” is also a syntactically correct candidate, since the latter is not semantically correct one.

3 Markov Chain Models for Compound Nouns

We suppose that compound nouns have statistical tendencies among their participants. The statistical tendencies considered are the sequence of participants’ semantic features and the sequence of participants’ lengths. Once the tendencies have been chosen to be incorporated in Markov chain, some Markov assumptions should be made. We adopted trigram assumptions considering the size of training data and the average number of participants in Korean compound nouns. When more than one sequence tendencies are used (in our case, two sequence tendencies), one Markov chain which covers multiple tendencies would have so many states that immense size of learning data is required. Moreover if each tendency has a low dependency on the others, it may cause waste of states in the Markov chain, resulting in lack of consistency. In such a case, multiple Markov chains are considered independent and probability can be calculated accommodating this assumption.

Assumption 1 (Trigram Assumption) For given a participant in a sequence of participants in a compound noun, any other participant but the two left-nearest ones can not have any statistical tendency with that given participant.

We will define some notations which will be used. \(S^i\) is the set of states in a Markov chain for the sequence of participant’s length. \(s^i(u,v)\) is a state in \(S^i\). If \(s^i_u\) is used, \(l\) means the participant’s sequence index, and if \(s^i_{(u,v)}\) is used, \(u\) is the previous participant’s length and \(v\) is the current participant’s length, since trigram Markov model is assumed. In the same way, \(S^{y}, s^{y} \) and \(s^{y}_{(u,v)}\) can be defined for the Markov chain of the sequence of participant’s semantic feature except that \(u\) means the previous participants’ semantic features and \(v\) means the current participant’s semantic feature. In addition, \(S\) is defined as \(S = S^i \otimes S^y\) and \(s\) is a state in \(S\).

Given a candidate decomposition of compound noun string \(w_1 \cdot w_2 \cdot \ldots \cdot w_n\) where \(w_i\) is ith participant, there are two most likely state paths \(s_1, \ldots, s_n\) from \(S^i\) and \(s^{y}_1, \ldots, s^{y}_n\) from \(S^{y}\). The calculation of the probability \(P(w_1 \cdot w_2 \cdot \ldots \cdot w_n)\) for the selection among candidates decompositions can be, \(P(s_1, \ldots, s_n) = \)
With this assumption, for example, given a compound noun "대학생신조회모임", any candidate which have the prefix decomposed as "대학생" + "신조회" is preferred to all candidate which have the prefix decomposed as "대학" + "신 + 조회".

While decomposition is performed, so long as candidate prefixes decomposed have the same total syllable length, all the candidates prefixes other than least word participants prefix need not be reserved any longer for the decomposition of the remaining suffix. Markov assumption as well enables the composition process to ignore prematurely all the candidates which are not searched with yet but prefixed with lower probabilities provided candidate prefixes have the same total syllable length and reach at the same state in the Markov chain.

Generally speaking, if some conditions could be satisfied, dynamic programming method can be applied to the problem in exponential search space with two assumptions mentioned. These kinds of assumptions make the search method systemic and efficient.

### 4 Decomposition Algorithm

While decomposition is performed from left to right, the left substring of the last composition point will be referred to the prefix of that partially decomposed candidate. Given a noun string N₁ of length l, the leftmost participants N₁ of N₁ are looked up in dictionary and the semantic features of them are also got. N₁ are inserted in the sorted list or heap by their length. And then, the candidate which has the shortest prefix is picked up and the next decomposition point is sought and inserted in the sorted list like the first process. But except the first process, insertion must be entailed by the verification of the assumptions mentioned above, namely some prefixes which have no possibility to be the best candidate are cannot inserted in the candidate pool. This process is repeated till all the prefixes have the length l. The candidates remained at this point are compared using Markov chain and the best one is returned. Overall Decomposition algorithm is described below.

**Algorithm 1 Decompose(N₁)**

1. Insert prefixes of N₁ in Pool \( \triangleright \) prefixes must be registered in dictionary
2. while \( k < l \), for all \( N₁ \in \text{Pool} \) do \( \triangleright \) subscript means prefix length
4. Prefix \( \leftarrow \text{Pool}.\text{remove}() \) \( \triangleright \) pick up the shortest prefix
5. Str \( \leftarrow N₁ - \text{Prefix} \) \( \triangleright \) Str contains suffix of N₁ without Prefix
6. while Str in dictionary.
7. Generate all concatenations of Prefix and prefixes found at 6
8. Insert concatenations generated at 7 in Pool.
9. return candidates in Pool maximizing Eq(1)
In the algorithm presented above, "insert in Pool" deserves to be revisited. When insertion into Pool are performed, Markov assumption and least word participants assumption are applied and candidates not appropriate are not inserted or are removed from Pool. Pool are always sorted by prefix length so that candidates having the same prefix length may be applied to the assumptions easily when insertion is performed. If conditional insertion and removal didn't take place, our algorithm would find all the candidate decompositions. In comparison with other algorithms, our algorithm cannot miss the best decomposition unless the least word participants preference assumption fail.

5 Experimental Results

Experiments have been performed in two ways and will be commented. One is learning of Markov chains and the other is compound noun decomposition using learned Markov chain matrices. Markov chains were trained on a set of 20564 compound nouns which are decomposed by humans. These nouns were extracted from HTML documents in home pages of several newspaper corporations. Some nouns may have postpositions as a suffix. The distribution of training data are given in Tables (1)-(3).

Table 1: Distribution of features in the training data

<table>
<thead>
<tr>
<th>Semantic feature</th>
<th>Usage frequency</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>14684</td>
<td>26.4</td>
</tr>
<tr>
<td>Action</td>
<td>10075</td>
<td>18.2</td>
</tr>
<tr>
<td>Postposition</td>
<td>9787</td>
<td>17.7</td>
</tr>
<tr>
<td>Concrete</td>
<td>4535</td>
<td>8.2</td>
</tr>
<tr>
<td>Location</td>
<td>4499</td>
<td>8.1</td>
</tr>
<tr>
<td>Human</td>
<td>4297</td>
<td>7.8</td>
</tr>
<tr>
<td>Suffix</td>
<td>3509</td>
<td>6.9</td>
</tr>
<tr>
<td>Proper Noun</td>
<td>1716</td>
<td>3.1</td>
</tr>
<tr>
<td>Prefix</td>
<td>1023</td>
<td>1.8</td>
</tr>
<tr>
<td>Temporary</td>
<td>668</td>
<td>1.2</td>
</tr>
<tr>
<td>Number</td>
<td>338</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Now let $L(x)$ and $F(y)$ be random variables. $L(x)$ corresponds to the distribution of the length of participant syllables and $F(y)$ to the distribution of the semantic feature of the participant. Let $ML(x)$ be a random variable representing the distribution of the transition from $s_{i(x)}^l$ to $s_{(x,j)}$ for all $i,j$ and $MF(y)$ be a random variable representing the distribution of the transition from $s_{i(x)}^l$ to $s_{(x,j)}^f$ for all $i,j$.

If Markov chains trained by training data are to have any usefulness and semantic feature set $i$: to be well organized, $L(x)$ distribution and $F(y)$ distribution is believed to be different from $ML(x)$ and $MF(y)$ respectively. As a measure of these, here, relative entropy or Kullback-Leibler divergence is proposed and measured. The relative entropy is given by [8]

$$D(p||q) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)}$$

We calculated $D(ML(x)||L(x))$ and $D(MF(y)||L(y))$ and we got

$$D(ML(x)||L(x)) = 0.64$$
$$D(MF(y)||F(y)) = 2.1$$

This result above means that the Markov chain for the sequence of participants' semantic features is more informative than that of the Markov chain for the sequence of participants' lengths. Relative entropy can be compared and used to select which tendency to utilize. We suggest that feature set might be organized through the comparison of relative entropy.

To evaluate the performance of our method, 5027 compound nouns not related with training data are extracted from web documents and experimented with. No running data has any proper noun not registered in dictionary for evaluating maximum performance. The results are shown in Table 4.

Given the same test data, the longest match first method achieved precision of 90.2% and recall of 100%. The best accuracy of the other methods announced ranks up to 99%. The comparison among other methods shows that our method is not less accurate than the best one proposed before, considering that our test data may have postpositions, suffixes or prefixes.
Table 4: Recall and precision for the distribution of 5027 compound noun decomposition

<table>
<thead>
<tr>
<th></th>
<th>Markov chain used</th>
<th>not Markov chain used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recall (%)</td>
<td>91.5</td>
<td>100</td>
</tr>
<tr>
<td>Precision (%)</td>
<td>99.7</td>
<td>98.4</td>
</tr>
</tbody>
</table>

6 Conclusion

We presented a method for the decomposition of compound nouns that uses the statistics of syllable length and semantic feature of their participants. We used two assumptions in compound noun decomposition. The first is least participants preference assumption and trigram assumption of the state sequences in word lengths and semantic features. The first assumption alone could achieve a good accuracy but could not cover some training data when ambiguity occurs. The combined method covered the rest and increased recall up to 100% and overall accuracy rate to 98.4 for the data set of 5027 compound nouns extracted from web documents.

Future work can be done in two directions. One is to define a good feature set since it is believed that accuracy rate depends strongly on feature set organization. We have proposed that relative entropy could be a measure for finding a good set of semantic features. Another direction for future work is to deal with the compound noun which contains unregistered nouns. Unregistered nouns frequently shows up in compound nouns. The probability and patterns for unregistered nouns should be defined and learned in some way and the algorithm for this should be studied to find unregistered nouns.

References


